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Invited Review

Operations research for sustainability assessment of products: A review

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ABSTRACT

The environmental and social impacts of products are being increasingly scrutinized. This necessitates systematic assessment methods. Life Cycle Sustainability Assessment (LCSA) provides a framework to addresses diverse sustainability issues over the product's life cycle, but its application is complicated. Major challenges, such as the selection of relevant indicators, multi-criteria comparisons of alternatives, the treatment of uncertainties, or the integration of spatially differentiated data, can be facilitated by adopting advanced analytical methods from Operations Research. This paper reviews 142 articles that use Operations Research methods for product-related sustainability assessments. The articles were selected from peer-reviewed scientific literature in a systematic search and screening process. Descriptive analysis shows that related publication output is growing over time and originates mainly in journals related to Environmental Management. While ecological indicators are considered by most articles, the integration of economic and social indicators is emerging. Focusing on the contributions of Operations Research, a detailed analysis shows that more than half of the articles adopt methods from Multi-Attribute Decision Making (MADM), followed by Data Envelopment Analysis (DEA) and Multi-Objective Decision Making (MODM). Uncertainties with regard to inventory data and decision makers' preferences are addressed using fuzzy logic, stochastic models, or sensitivity analysis. The use of spatially differentiated data is not frequently found in the reviewed articles. Research needs derived from this analysis comprise the integration of qualitative and semi-quantitative (social) indicators, the simultaneous consideration of global and local sustainability objectives, and the application of systematic procedures to address uncertainty.

1. Introduction

Sustainability assessment refers to the systematic compilation and evaluation of environmental, economic, and social impacts related to a system. It aims at providing information that supports improving the system or comparing it to other systems. Sustainability assessments have been carried out for different systems including countries, industries, technologies, companies, and products (Munda, 2016; Ness, Urbel-Piirsalu, Anderberg, & Olsson, 2007; Zamagni et al., 2009). This article focuses on the assessment of product-oriented systems (comprising goods and services), a branch of sustainability assessment that is receiving increasing attention because the function, quality, availability, and aesthetics of products are no longer the only determinants for their value. Instead, their impact on the environment and the social consequences of their production are also taken into consideration. Consequently, much attention is directed on methods to trace and estimate the sustainability of products, capturing their economic, environmental, and social impacts.

Systematic approaches to assess product sustainability are based on two key principles: life cycle thinking and the triple bottom line concept. Life cycle thinking requires assessing the impacts over the entire life cycle of a product "from cradle to grave". The triple bottom line concept stresses the importance of simultaneously taking into account ecological, economic, and social sustainability impacts. Both principles are integrated into the comprehensive framework of Life Cycle Sustainability Assessment (LCSA) (Kloepffer, 2008; UNEP/SETAC, 2011).

LCSA builds on established methods like (environmental) Life Cycle Assessment (LCA), (economic) Life Cycle Costing (LCC), and Social Life Cycle Assessment (SLCA). The procedure of the assessment is derived from the ISO 14040/14044 standards (Fig. 1). A typical LCSA study starts with the definition of the goal and the scope. Next, inventory data describing the exchanges between the unit processes in the product's life cycle and their executing organizations as well as the external environment is collected. In the

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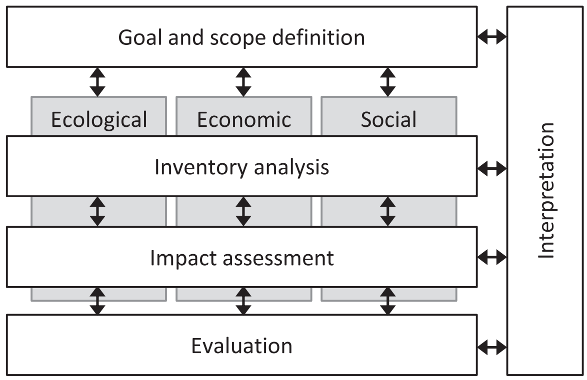

Fig. 1. Framework for Life Cycle Sustainability Assessment (adapted from ISO 14040:2006).

subsequent impact assessment, the inventory data is assigned to ecological, economic, and social impact categories. Finally, an evaluation step integrates the various indicators from all three sustainability dimensions to support decision making, taking into account the decision makers' preferences and the underlying uncertainty (Grubert, 2017; Keller, 2015). All steps are accompanied by interpretation and may be carried out in an iterative procedure as new insights, data limitations, or stakeholder views can lead to a redefinition of the study focus, goal, and methods (UNEP/SETAC 2011).

Although sustainability assessments of products are quite common in industry, and standard approaches are recognized in the scientific community, major unresolved problems in these assessments have been identified (for LCA see, e.g., Reap, Roman, Duncan, & Bras, 2008). *First*, the selection of indicators and impact categories that are relevant for the assessment is a delicate task that involves tradeoffs between comprehensiveness and data availability and collection effort. *Second*, the comparison of different products, alternative product designs, or supply chains of a product is often difficult because it necessitates normalization and weighting of multiple and typically incommensurable assessment criteria. *Third*, the handling of uncertainty and incomplete data is a major issue in sustainability assessment where little guidance is available. *Fourth*, spatial differentiation to account for the heterogeneity in technologies and the environment across different regions is often desired but rarely implemented as it requires ample data and appropriate methods to process it.

To deal with the problems discussed above and to make sustainability assessment an effective tool to support decision-making necessitates the application of advanced analytical methods. The objective of this paper is therefore to review the use of Operations Research methods to facilitate sustainability assessment of products. The review is based on 142 conceptual and application-oriented articles from scientific literature that have been selected in a systematic search and screening process. Our analysis aims at highlighting the boundaries of knowledge and identifying potential research gaps. This review differs from previous publications in its systematic search procedure, the focus on product-related sustainability assessments, and the exclusive analysis of articles that apply Operations Research methods to facilitate the assessment. We seek to make a valuable contribution by providing a structured overview of the literature published in this field and to identify areas that require further consideration.

The existing literature on sustainability assessment has been summarized from different perspectives. Ness et al. (2007) provide a general framework to categorize tools for sustainability assessment. Each tool is introduced briefly and selected applications are discussed. More detailed reviews can be found for specific tools. Focusing on environmental sustainability, Finnveden et al. (2009) discuss the methodological developments in LCA, and Gaussin et al. (2013) survey existing approaches for assessing the environmental footprint of manufactured products. Approaches to monetary valuation in LCA are discussed by Pizzol et al. (2015), and applications of LCC are reviewed by Korpi and Ala-Risku (2008). With regard to the social dimension, Jørgensen, Le Bocq, Nazarkina, and Hauschild (2008) give an early overview of methodologies used in SLCA, and the more recent review by Petti et al. (2016) investigates applications of SLCA.

An early discussion on the application of Operations Research models in the context of Environmental Management is given in Bloemhof-Ruwaard, van Beek, Hordijk, and van Wassenhove (1995). Approaches in Management Sciences and Operations Research to air pollution management with a focus on mathematical programming are surveyed in Cooper et al. (1997). The state-of-the-art in sustainability analysis methodologies for efficient decision support has been summarized by Liu, Leat, and Smith (2011). The use of multi-criteria decision analysis in environmental sciences is reviewed by Huang, Keisler, and Linkov (2011) and Cegan et al. (2017). A review by Zanghelini et al. (2018) discusses how multi-criteria decision analysis can aid results interpretation in LCA. Recent reviews on Operations Research and Sustainable Supply Chain Management have been published by Brandenburg, Govindan, Sarkis, and Seuring (2014), Seuring (2013), Tang and Zhou (2012), and Barbosa-Póvoa, da Silva, and Carvalho (2018). While these papers focus on the integration of sustainability aspects into Operations and Supply Chain Management models, little attention has been given to structure the literature on the use of Operations Research models within product-related sustainability assessment, despite the manifold contributions that have been made in this area.

The remainder of this paper is organized as follows. The methodology of this literature review is described in Section 2. Aggregate descriptive analyses of the review database are presented in Section 3 and detailed analyses of article clusters based on Operations Research methods are carried out in Section 4. From the results of these analyses, promising approaches and research needs are identified in Section 5 and conclusions are presented in Section 6.

2. Review methodology

A systematic search procedure was applied to ensure comprehensiveness and to minimize potential bias in selecting relevant articles. Based on the research questions defined in Section 1, appropriate keywords were identified and combined into a multi-level search string. The structure of the search string is illustrated in Fig. 2. It includes keywords that are related to the *context* (sustainability assessment), the *subject* (products), and the *methods* (from Operations Research). With regard to the methods, two complementary search strategies were applied: *Search I* identifies articles that mention specific Operations Research methods in their title, abstract, or keywords, and *Search II* includes articles that have been published in journals that are listed in the top quartile of the Management Science and Operations Research category in the Scimago Journal and Country Rank (www.scimagojr.com). The searches were first carried out in August 2016 and updated in November 2017 using Elsevier's Scopus database (www.scopus.com), which provides extensive coverage of peer-reviewed scientific literature and offers an advanced interface for detailed analysis and data export (Harzing & Alakangas, 2016; Moed et al., 2016).

The results from the database search were analyzed in a structured screening process. First, formal criteria were applied to include only articles that are written in English and published in peer-reviewed scientific journals. Next, the abstracts were checked for content-related criteria, namely that the article is related to

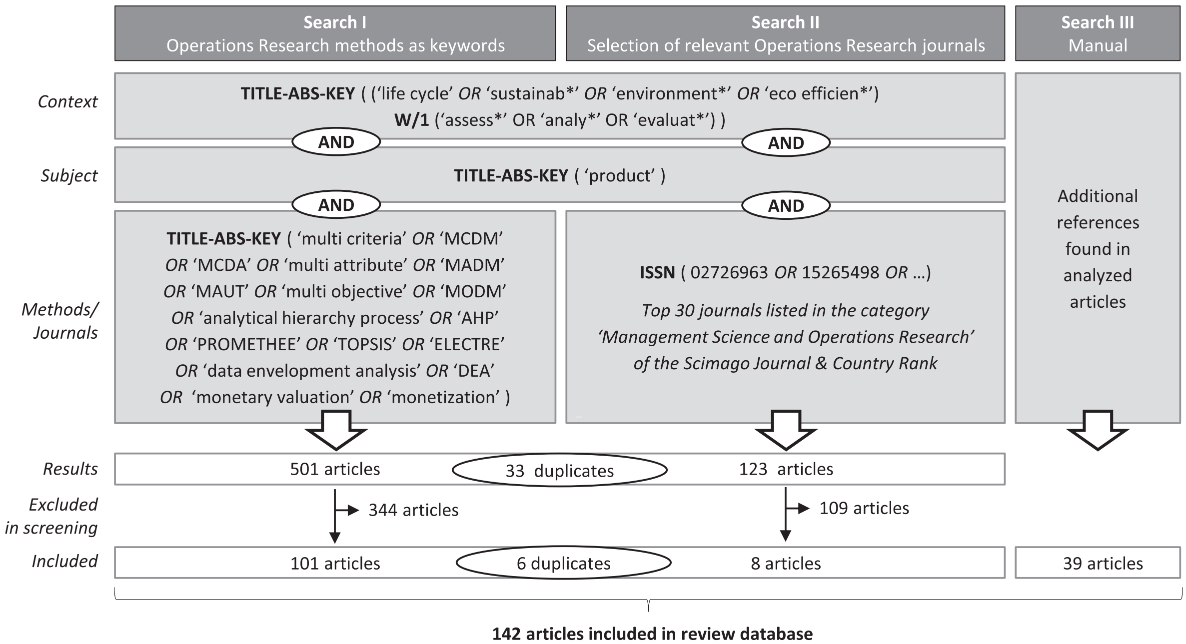

Fig. 2. Overview of search strategies and results.

sustainability assessment, that it addresses a product, and that the assessment is facilitated by Operations Research methods. Self-contained sustainability assessments of companies, industries, countries, or policies are not in the scope of this review and articles covering these aspects were only considered if they are strongly related to a product. For the articles remaining in the review database, the full texts were retrieved and analyzed using a structured questionnaire to extract the relevant data. Additional references that had been identified during this step were added to the review database (Search III), resulting in a total of 142 articles that are included for further analysis.

3. Descriptive analysis of the review database

For a descriptive analysis of the review database, we have tallied the publication output over time, compiled the contributing journals, reviewed the products considered, and listed the sustainability dimensions and indicators used in the articles. An overview on the application of Operations Research methods as well as the treatment of uncertainties and spatial differentiation is also given as a starting point for a more detailed elaboration on these topics in Section 4.

Fig. 3 illustrates the number of articles in this review by publication year. The growth in the number of publications over time reflects an increasing deployment of Operations Research methods to facilitate sustainability assessment of products. This parallels the development of LCA (Guinee et al., 2011). Before 1990, LCA was in the phase of conception and a common theoretical framework was missing. The focus of the 1990s was then on standardization and first scientific journal articles were published. Not surprisingly, the earliest article on the use of Operations Research methods in sustainability assessment of products found in the review database is from 1995 (Bloemhof-Ruwaard, Koudijs, & Vis, 1995). The authors apply multiple Operations Research methods: Analytic Hierarchy Process (AHP) to aggregate environmental effects into a single score and linear programming to improve this score by optimizing the product composition. The focus of the reviewed articles from this period is clearly on environmental issues, but efforts to integrate economic aspects start to emerge (Azapagic & Clift, 1998, 1999).

During the 2000s, LCA received ever-increasing attention (e.g., UNEP/SETAC launch Life Cycle Initiative, European Commission communicates Integrated Product Policy), life cycle-based carbon

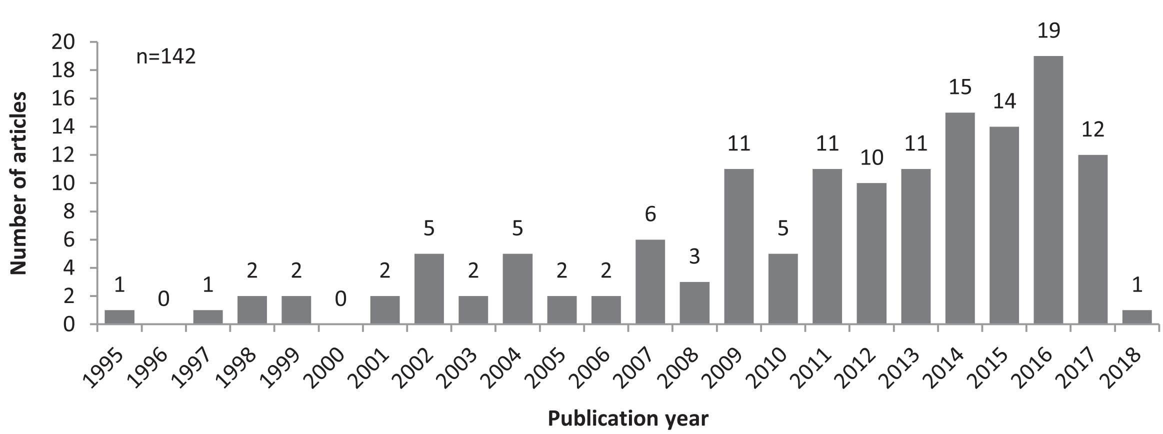

Fig. 3. Distribution of articles by publication year.

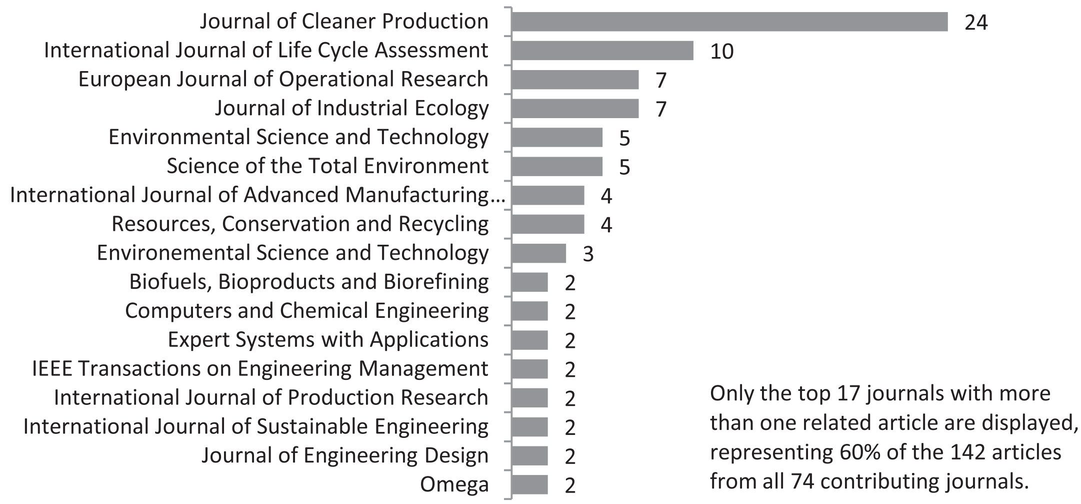

Fig. 4. Distribution of articles by contributing journals.

footprint accounting was on the rise, and diverging approaches in LCA were developed, such as dynamic LCA, spatially differentiated LCA, risk-based LCA, and consequential LCA. The introduction of SLCA and LCSA also took place in that decade, with considerable developments in the 2010s (Guinee et al., 2011). Over the past decade, sustainability assessment has become considerably complex (more indicators, broader scope), highlighting the need for systematic decision support based on Operations Research methods.

The integration of Operations Research methods into sustainability assessment has been advanced mainly by the Environmental Management community, as can be concluded from the analysis of the contributing journals (Fig. 4). The 142 articles under review were found in 74 different journals. While 17 journals contained more than one related article, 57 journals contributed one single article each. The majority of all 74 journals is related to the Environmental Management domain. Only 7 journals belong to the Management Science and Operations Research field (according to SJR journal ranking 2015), namely European Journal of Operations Research, International Journal of Production Research, Omega, International Journal of Production Economics, Journal of Loss Prevention in the Process Industries, Journal of the Operational Research Society, and Computers and Operations Research. With a total of 7 articles, the European Journal of Operational Research is in the top 3 of contributing journals, being only surpassed by the Journal of Cleaner Production (24 articles) and the International Journal of Life Cycle Assessment (10 articles). This supports the premise that sustainability assessment can be seen as an emerging application area of Operations Research.

The application areas for sustainability assessment are quite diverse (Fig. 5). Most often, electronic products have been assessed (29 articles), which might be due to the high regulatory pressure from legislation in this field (e.g., Directive of Waste Electrical and Electronic Equipment (WEEE) in the European Union). Chemicals (16 articles), materials (16 articles), electricity (15 articles), food (13 articles), cars (10 articles), industrial machines (9 articles), packaging (8 articles), buildings and consumer products (7 articles each), and fuels (6 articles) have received significant attention.

A look at the sustainability dimensions and indicators addressed by the articles reviewed reveals that almost all consider at least the ecological dimension of product-related impacts (Fig. 6). Related articles concentrate on the ecological dimension alone (60 articles) or integrate the ecological dimension with the economic (52 articles) or social dimension (2 articles). There are 25 articles in which all three dimensions of sustainability are assessed simultaneously. Two articles focus on the social dimension, and one article addresses the social and the economic dimension of sustainability. Articles with a purely economic focus are not considered in the scope of this review.

Within the ecological dimension, the most commonly-used indicator is the global warming potential (78 articles). Other popular ecological indicators are acidification potential (51 articles), toxicity potential (48 articles), photochemical oxidant formation potential (41 articles), eutrophication potential (41 articles), and resource depletion potential (38 articles). The choice of indicators is often related to the impact assessment method. Frequently-used

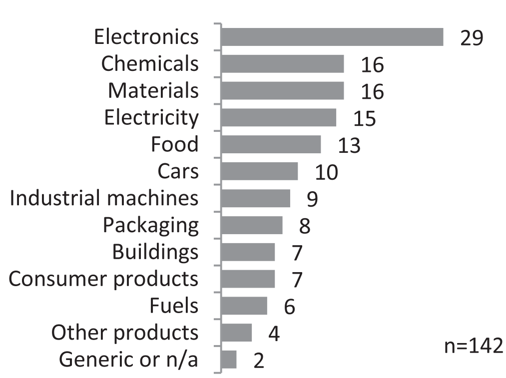

Fig. 5. Distribution of articles by product category.

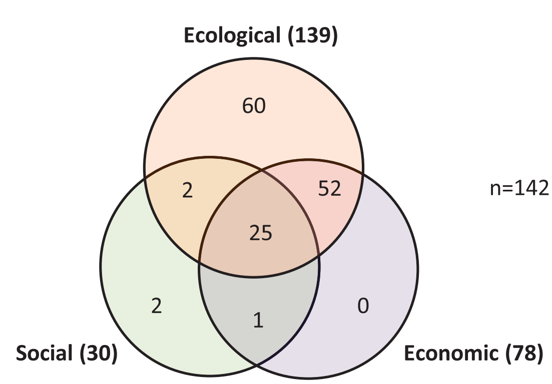

Fig. 6. Distribution of articles by sustainability dimension.

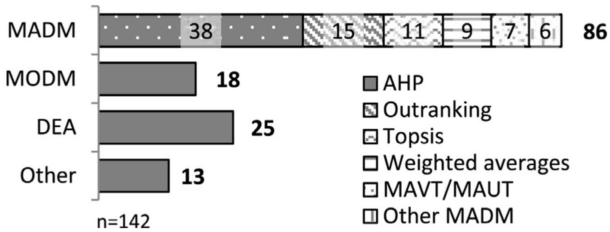

Fig. 7. Distribution of articles by Operations Research method.

methods are, for instance, Eco-indicator 99, ReCiPe 2008, or TRACI. The economic dimension is dominated by cost-oriented indicators (47 articles). A smaller number of articles uses price-oriented indicators (10 articles), profit-oriented indicators (7 articles), or indicators considering the added value of the life cycle stages (5 articles). Regarding the social dimension, the variety of indicators is even larger. Most often, indicators regarding the stakeholder group "workers" (16 articles) are used, followed by "society" and "local community" (10 articles each), "consumers" (7 articles), and "value-chain actors" (3 articles). Overall, the average number of indicators used in the articles is 9.5 and the median value is 7.0. While 103 articles consider 10 or less indicators, there is one article integrating 44 indicators and one article integrating 75 indicators in the assessment. A detailed list of the indicators that are applied in each article can be found in the supplementary material (Table S1).

The multiplicity of indicators considered in the reviewed articles underscores the need for the application of Operations Research methods to obtain and interpret results when conducting the sustainability assessment. These methods can be categorized into three main groups according to the purpose and the setting of the assessment (Fig. 7). Multi-Attribute Decision Making (MADM) methods are applied to evaluate a finite set of alternatives based on multiple criteria (attributes), Multi-Objective Decision Making (MODM) methods are applied to identify and evaluate Pareto optimal solutions on the efficient frontier of a mathematically constrained solution space, and Data Envelopment Analysis (DEA) is applied to analyze the relative efficiency of a sample of alternatives if the efficient frontier is unknown. MADM methods represent the largest group and are adopted by 86 articles to facilitate comparisons of alternative products, designs, or processes. Within this group, the most frequently applied methods are the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), outranking methods such as Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) or Elimination Et Choix Traduisant la Réalité (ELECTRE), Simple Additive Weighting (SAW), and Multi-Attribute Value/Utility Theory (MAVT/MAUT). MODM methods are adopted by 18 articles, mainly focusing on product design. DEA models are used in 25 articles to assess the eco- or socio-efficiency of products based on a limited number of typically incommensurable

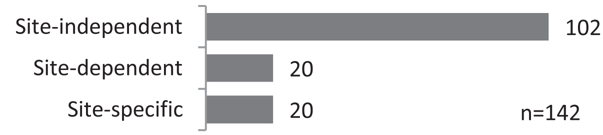

Fig. 9. Distribution of articles by level of spatial differentiation.

indicators. Furthermore, there are 13 articles that apply a variety of methods that cannot be assigned to one of the above groups.

Fig. 8 shows that uncertainty is considered in more than half of the articles, mainly with regard to the inventory data (15 articles) and the decision makers' preferences (34 articles), or both (22 articles). Uncertain inventory data is typically related to the variability in input and output flows (e.g., spatial differences, seasonal changes) while uncertain preferences are deduced from the variability across decision makers regarding the priority of assessment criteria. The most common method used in the reviewed articles to address uncertainty is sensitivity analysis (45 articles), followed by fuzzy logic (26 articles) and (Monte Carlo) simulation (16 articles).

The level of spatial differentiation is addressed in Fig. 9. The assessments in 102 articles are site-independent, meaning that average data not related to specific geographic locations is used. Only in 20 articles, site-dependent data reflecting the regional conditions of the assessment is used, and in 20 articles, site-specific assessments are carried out.

Details on the Operations Research methods, the treatment of uncertainties, and the spatial differentiation are provided in the supplementary material (Table S1) and discussed in Section 4.

4. Application of Operations Research methods in sustainability assessment

The following discussion is structured into four sections that are related to the different families of Operations Research methods. Within each section, the typical application scenarios of the methods in the context of sustainability assessment are described. Moreover, we deliberate the methods' capabilities to cope with the challenges illustrated in Section 1 and highlight articles with promising approaches. Finally, we point at shortcomings of the methods to derive research needs.

4.1. Multi-Attribute Decision Making (MADM)

MADM models are used to make comparisons based on multiple criteria (attributes) within a set of discrete alternatives. They are particularly useful when the number of attributes is large and the number of alternatives is moderate. A variety of MADM model that differ with respect to input data and aggregation procedures has been developed (Guitouni & Martel, 1998; Seppälä, Basson, & Norris, 2001).

MADM models have been applied in 86 articles of this review (Table 1). Their ability to handle a large number of attributes

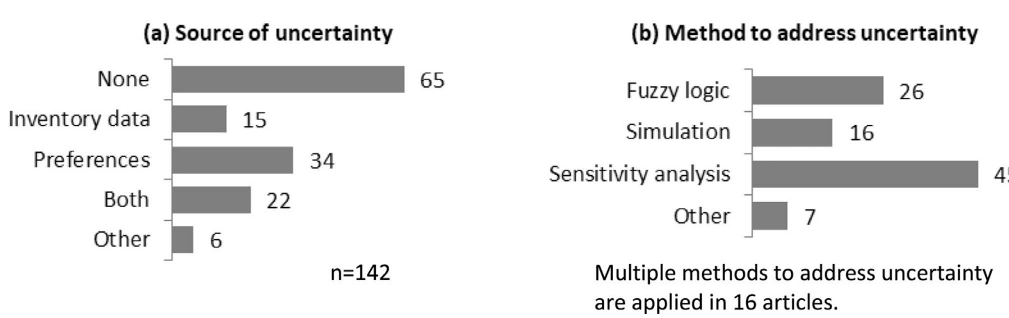

Fig. 8. Distribution of articles by (a) source of uncertainty and (b) method to address uncertainty.

Table 1
Overview of articles applying MADM methods.

Authors and Year	Product	ECOL	ECON	SOC	Attributes	Alternatives	Methodological features
Weighted averages							
Klein (2013)	Electricity (solar power system)	x	x	–	5	6	–
Ma and Okudan Kremer (2015)	Gasoline engine	x	x	x	5	7	Left-right fuzzy ranking
Miettinen and Hämäläinen (1997)	Aluminum cans	x	–	–	4	8	–
Milani et al. (2011)	Plastic gears	x	x	–	3	2	Signal-to-noise ratio
Park et al. (2006)	Washing machine	x	x	–	2	14	–
Pask et al. (2017)	Industrial ovens	x	x	x	7	3	Fuzzy sets, Monte Carlo Simulation
Roth et al. (2009)	Electricity (generation technologies)	x	x	x	75	18	–
Volkart et al. (2016)	Electricity (generation technologies)	x	x	x	18	26	–
Wulf et al. (2017)	Rare earth permanent magnets	x	x	x	28	3	Linear and geometric aggregation
MAVT/MAUT							
Azapagic et al. (2016)	Electricity (generation technologies)	x	x	x	36	4	MAVT, integration of AHP
Azkarate et al. (2011)	Milling machine	x	x	x	9	3	MAVT
Eddy et al. (2013)	Charcoal grill	x	x	–	10	7	MAUT
Rochat et al. (2013)	PET bottles	x	x	x	3	4	MAUT, material flow analysis
Scott et al. (2016)	Carbon nanotubes for PV modules	x	x	–	7	3	MAUT, Monte Carlo simulation
Subramanian et al. (2017)	Nano-enabled biocidal paint	–	–	x	12	1	MAVT
Tsang et al. (2014)	Lumber treatment	x	x	–	14	6	MAVT
AHP							
Agarski et al. (2016)	Food waste	x	–	–	5	4	Fuzzy AHP
Ahmed Ali, Sapuan, Zainudin, and Othman (2015)	Natural fiber reinforced composites	x	x	–	7	8	–
Avram et al. (2011)	Machine tool	x	x	–	6	24	–
Bereketli Zafeirakopoulos and Erol Genevois (2015)	Hand blender	x	–	–	11	6	ANP
Bloemhof-Ruwaard, Koudijs et al. (1995)	Fat blends	x	–	–	9	8	AHP + Linear programming
Chakroun, Gogu, Pacaud, and Thirion (2014)	Spreader for composted products	x	–	–	14	5	–
Chan et al. (2014)	Personal electronic products	x	x	–	9	4	Fuzzy AHP
Chan et al. (2013)	Electronic products	x	–	–	5	4	Fuzzy AHP
De Luca et al. (2015)	Citrus fruits	x	x	x	44	9	Social LCA, participatory approach
Eagan and Weinberg (1999)	Aluminum	x	–	–	6	2	–
García-Diéguez et al. (2015)	Footwear	x	–	–	3	4	Fuzzy AHP, Monte Carlo simulation
Ghadimi et al. (2012)	Car fuel filter	x	x	x	7	2	Fuzzy AHP
Gloria et al. (2007)	Building products	x	–	–	12	–	–
Hafizan, Noor, Abba, and Hussein (2016)	Electricity (generation technologies)	x	–	–	17	3	–
Hermann, Kroeze, and Jawjit (2007)	Pulp (for paper industry)	x	–	–	5	1	–
Hosseinijou et al. (2014)	Building materials	–	–	x	30	2	–
Huang and Ma (2004)	Packaging materials	x	–	–	7	9	Cluster analysis
Jiang, Zhang, and Sutherland (2012)	Valve system	x	–	–	6	4	–
Kengpol and Boonkanit (2011)	Air conditioners	x	x	x	18	5	ANP
Khan et al. (2002)	Urea	x	x	–	17	4	Fuzzy Composite Programming
Kim et al. (2009)	Home appliances	x	x	–	10	6	–
Kim and Moon (2017)	Cofee maker	x	x	x	6	3	Grey relational analysis, Bayesian network
Lipušček et al. (2010)	Wood products	x	–	—	28	–	Delphi method
Lye et al. (2002)	Coffee maker	x	x	–	10	20	–
Myllyviita et al. (2013)	Wood-based bioenergy	x	x	x	8	3	Modified AHP
Myllyviita et al. (2014)	Houses	x	–	–	3	3	Comparison of SWING, SMART, AHP
Ong, Koh, and Nee (2001)	Plates	x	–	–	30	2	–
Ordouei, Elkamel, Dusseault, and Al-Hajri (2015)	Gasoline blends	x	x	–	6	3	–
Pineda-Henson et al. (2002)	Pulp (for paper industry)	x	–	–	7	4	–
Pineda-Henson and Culaba (2004)	Semiconductors	x	–	–	7	5	–
Ramanujan et al. (2014)	Mining equipment	x	–	–	6	8	Stochastic AHP
Ramzan et al. (2008)	Distillation column	x	–	–	11	1	–
Sadiq and Khan (2006)	Urea	x	x	–	17	4	Fuzzy composite programming
Sabaghi et al. (2016)	Generic	x	x	x	13	1	Fuzzy AHP
Shao, Taisch, and Ortega Mier (2016)	Car	x	–	x	16	–	–

(*continued on next page*)

Table 1 (*continued*)

Authors and Year	Product	ECOL	ECON	SOC	Attributes	Alternatives	Methodological features
Wang, Chan, Lee, and Li (2015a)	Consumer electronic products	x	–	–	5	4	–
Wang et al. (2014)	Electronic product	x	–	–	5	4	Fuzzy ANP
Yu, Zhixian, and Zhiguo (2007)	Chemical products	x	x	–	11	2	–
TOPSIS							
Chiang et al. (2011)	Optical mouse	x	–	–	5	5	Back-propagation neural networks
Feng and Mai (2016)	Milling machines	x	x	x	19	6	Triangular fuzzy numbers
Gao et al. (2010)	Soybean crusher	x	x	–	11	8	Triangular fuzzy numbers, integration of AHP
Huang, Zhang et al. (2011)	PC housing materials	x	x	–	2	8	Entropy method
Kucukvar et al. (2014)	Pavements	x	x	x	16	4	Intuitionistic fuzzy sets
Ng and Chuah (2012)	Electric appliances	x	–	–	5	4	Triangular fuzzy numbers, integration of AHP
Onat et al. (2016)	Alternative passenger vehicles	x	x	x	16	7	Intuitionistic fuzzy sets
Pires et al. (2015)	Packaging materials	x	–	x	12	13	Integration of AHP
Tian et al. (2016)	Personal electronic products	x	–	–	5	4	Neutrosophic linguistic numbers
Wang and Chan (2013)	Automotive alternator	x	x	x	4	4	Triangular fuzzy numbers, fuzzy extent analysis
Wang et al. (2015b)	Wireless electronic products	x	–	–	20	4	Triangular fuzzy numbers
Outranking							
Boufateh et al. (2011)	T-shirt	x	–	–	10	3	PROMETHEE I, GAIA
Canis et al. (2010)	Carbon nanotubes	x	x	–	5	4	Stochastic multi-attribute analysis
Cinelli et al. (2017)	Silver nanoparticles	x	–	–	8	5	ELECTRE TRI, stoachstic multi-criteria acceptability analysis
Domingues et al. (2015)	Light-duty vehicles	x	–	–	10	6	ELECTRE TRI, constrained weights
Geldermann and Rentz (2005)	Mobile phones coating	x	x	–	8	9	PROMETHEE I&II
Gheorghe and Xirouchakis (2007)	Vacuum cleaners	x	x	–	4	3	Fuzzy outranking
Le Téno and Mareschal (1998)	Plaster wallboards	x	–	–	3	4	PROMETHEE I&II with intervals, GAIA
Parajuli et al. (2015)	Biomass	x	x	–	15	13	PROMETHEE I&II
Prado-Lopez et al. (2014)	Laundry detergent	x	–	–	18	2	Stochastic multi-attribute analysis
Rajagopalan et al. (2017)	Biofuels	x	–	–	9	4	Stochastic multi-attribute analysis
Rogers and Seager (2009)	Transportation fuels	x	–	–	6	5	PROMETHEE, stochastic multi-attribute analysis
Samani et al. (2015)	Composite construction materials	x	x	–	6	5	PROMETHEE II
Schmitt et al. (2017)	Food products	x		x	12	4	PROMETHEE I&II
Tervonen et al. (2009)	Nanomaterials	x	–	–	8	5	Stochastic multi-criteria acceptability analysis
Vukelic et al. (2017)	Knee support	x	x	–	7	3	PROMETHEE II, GAIA
Other MADM							
Bachmann (2013)	Electricity (generation technologies)	x	x	x	36	26	Dominating Alternative Algorithm
Benetto et al. (2004)	Electricity (from coal by-products)	x	–	–	9	6	NAIADE
Dhouib (2014)	Waste tires	x	x	x	4	5	Fuzzy MACBETH
Dorini et al. (2011)	Electricity (generation technologies)	x	x	x	22	2	Compromise programming, Monte Carlo simulation
Kadziński et al. (2018)	Silver nanoparticles	x	–	–	8	53	Ordinal regression
Naidu et al. (2008)	Silica nanoparticles	x	x	x	11	3	NAIADE

makes them a useful tool for the simultaneous assessment of multiple sustainability dimensions. While ecological and economic criteria are considered in 23 articles, social criteria are additionally integrated in 23 articles. MADM models are also used within Social Life Cycle Assessment. De Luca, Iofrida, Strano, Falcone, and Gulisano (2015) use a total of 44 mainly social indicators to compare different scenarios for citrus growing in Southern Italy, and Hosseinijou, Mansour, and Shirazi (2014) assess building materials based on 30 social indicators related to five stakeholder groups. In sustainabiliy assessments considering ecological, economic, and social criteria, up to 75 indicators have been applied (Roth et al., 2009). In contrast to the large number of attributes, the number of alternatives is usually moderate and does not typically exceed 20. Only in Lye, Lee, and Khoo (2002), 20 components of a coffee machine are analyzed regarding their specific contribution to the sustainability impact of the product, in Avram, Stroud, and Xirouchakis (2011), 24 different configurations of a machine tool system are compared, and in Bachmann (2013), 26 advanced electricity generation technologies are investigated.

A basic MADM method is the calculation of *weighted averages*, which is applied in 9 articles of this review. Miettinen and Hämäläinen (1997) discuss how LCA can benefit from decision analysis in both the planning of an LCA study and in the interpretation and understanding of the results. They suggest the use of a linear additive model for aggregating the criteria and the use of weight elicitations techniques like SMART (Simple Multi-Attribute Rating Technique) or AHP to integrate the stakeholders' preferences. Roth et al. (2009) and Volkart et al. (2016) compute weighted averages to aggregate sustainabiliy indicators in the context of electricity generation. Park, Tahara, Jeong, and Lee (2006) compare simple additive weighting as a representative of MADM methods to three other methods that integrate environ-

mental and economic aspects in the end-of-life stage of a washing machine. Milani, Eskicioglu, Robles, Bujun, and Hosseini-Nasab (2011) use simple additive weighting for combining environmental and economic criteria for plastic gear material selection into a single score. They adopt a signal-to-noise ratio to limit the direct compensation among criteria by means of their variability whereby a material with a high average score and a low standard deviation over all criteria receives highest preference. Wulf et al. (2017) test the influence of different normalization, weighting, and aggregation procedures when combining indicators of all three sustainability dimensions for the case of rare earth permanent magnets. Taking into account the uncertainty in design preferences, Ma and Okudan Kremer (2015) present a fuzzy logic-based approach to assess the sustainability of end-of-life options for components in the product design phase considering economic, environmental, and social indicators. Fuzzy operations and a left-right fuzzy ranking method (Chen and Hwang, 1992) are applied to derive weights for all sustainability criteria. Similarly, Pask, Lake, Yang, Tokos, and Sadhukhan (2017) use fuzzy set theory and Monte Carlo simulation to compute an aggregate fuzzy desirability indicator that allows for comparing alternative design options of an industrial oven.

In *Multi-Attribute Value Theory (MAVT)* and *Multi-Attribute Utility Theory (MAUT)***,** alternatives are first evaluated against each criterion using partial value or utility functions and the results are then aggregated over all criteria in an additive, multiplicative, or mixed way to obtain a global value or utility function. While MAVT is used for value measurement when there is no uncertainty about the consequences of the alternatives, MAUT explicitly considers that the consequences of the alternatives may be uncertain (Keeney & Raiffa, 1976; Seppälä et al., 2001).

Seven of the articles reviewed employ MAVT/MAUT for sustainability assessment. Tsang, Bates, Madison, and Linkov (2014) use MAVT to evaluate the benefits and risks of conventional and nano-enabled lumber treatment products. While their focus is on environmental and economic aspects, Subramanian et al. (2017) use MAVT in combination with SLCA to analyze the social aspects of a novel nano-copper oxide-based paint with biocidal functionality. Indicators from all three sustainability dimensions are integrated into an aggregate sustainability index using MAVT by Azapagic, Stamford, Youds, and Barteczko-Hibbert (2016) to compare alternative electricity generation scenarios and by Azkarate, Ricondo, Pérez, and Martínez (2011) to compare alternative designs of a machine tool. Eddy, Krishnamurty, Grosse, Wileden, and Lewis (2013) develop a Normative Decision Analysis Method for the Sustainability-Based Design of Products (NASDOP) based on MAUT, allowing taking into account the uncertainty associated with material and energy flows. They use this method to analyze potential alternatives of a charcoal grill based on both ecological and economic criteria. Rochat, Binder, Diaz, and Jolliet (2013) combine material flow analysis, LCA, and MAUT to support the selection of the best end-of-life scenario for polyethylene terephthalate (PET) bottles in Colombia. In this work, MAUT integrates ecological, economic, and social aspects in an analysis of the problem from a regional perspective. Scott et al. (2016) apply MAUT to the output of LCA to better understand the tradeoffs that exist in the adoption of different nanomaterials for photovoltaic modules from the public decision maker's perspective. By integrating Monte Carlo simulation, they are able to analyze the extent to which MAUT results are driven by scenario uncertainty resulting from the decision maker's perspective, production process uncertainties, and economic uncertainties.

The *Analytic Hierarchy Process (AHP)* is a popular MADM method developed by Saaty (1980) to elicit weights for each element in a hierarchical structure through pairwise comparisons. To this end, a pre-specified nine-point scale for quantifying verbal descriptions of preference among alternatives and importance among attributes is used (Seppälä et al., 2001). AHP has been applied for product sustainability assessment in 38 articles of this review. It is most often used in combination with LCA or SLCA to support the determination of weights when aggregating multiple indicators (e.g., Agarski, Budak, Vukelic, & Hodolic, 2016; Hafizan et al., 2016; Myllyviita et al., 2014). However, AHP can also be applied on its own when LCA results are replaced by expert judgements (e.g., Eagan & Weinberg, 1999; Lipušček et al., 2010).

While the common AHP formulation is based on unidirectional hierarchical relationships among decision levels, more complex interrelationships among decision levels and components can be modeled using the Analytic Network Process (ANP) (Saaty, 1996). ANP is also based on pairwise comparisons but allows for modeling more sophisticated decisions involving interactions and dependencies between alternatives and attributes that exist in real life problems (Bereketli Zafeirakopoulos & Erol Genevois, 2015). ANP is applied by Bereketli Zafeirakopoulos and Erol Genevois (2015) to identify the most significant environmental aspect of a hand blender in order to guide improvements in product design. Kengpol and Boonkanit (2011) use ANP for assessing product design improvement options for an air conditioner, and Wang, Chan, and White (2014) implement ANP to select the most environmentally sustainable design of electronic products.

AHP has also been combined with other Operations Research methods to increase its usefulness in specific applications. For example, Bloemhof-Ruwaard, Koudijs et al. (1995) apply LCA and AHP to evaluate the environmental impact of refined oils and incorporate the results into a linear programming blending model to determine optimal fat blends under consideration of certain availability constraints. Huang and Ma (2004) use cluster analysis to combine the rather qualitative judgments from AHP with the quantitative results from LCA. Kim and Moon (2017) combine AHP with grey relational analysis to compute a total sustainability indicator for a family of coffeemakers and use Bayesian network to analyze the risk to product redesign with regard to changes in components and sub-systems.

In some situations, it is difficult to express the pairwise comparisons of alternatives and criteria with crisp numbers due to lack of data or uncertainty in the decision maker's preferences. Nine of the articles analyzed integrate fuzzy logic into AHP. Quite frequently, linguistic terms used for pairwise comparisons are translated into fuzzy numbers that are further processed based on fuzzy logic. Agarski et al. (2016) propose a fuzzy-based methodology for impact category weighting in LCA based on both default and subjective weighting factors. Chan, Wang, White, and Yip (2013) use fuzzy AHP to evaluate the performance of alternative product designs, and Chan, Wang, and Raffoni (2014) combine LCA with fuzzy AHP as a tool for pre-screening product designs before a full LCA is conducted. García-Diéguez et al. (2015) develop a fuzzy AHP-based eco-design tool, which they apply to children's footwear. Ghadimi, Azadnia, Mohd Yusof, and Mat Saman (2012) use fuzzy AHP to weight selected elements and sub-elements for a more precise assessment and better decision support. Khan, Sadiq, and Husain (2002) and Sadiq and Khan (2006) propose a risk-oriented methodology for process plant design based on LCA and fuzzy composite programming involving AHP. Sabaghi, Mascle, Baptiste, and Rostamzadeh (2016) employ fuzzy AHP accompanied by Shannon's entropy formula to determine the relative importance of each element in the hierarchy. Wang et al. (2014) integrate fuzzy logic into ANP to support the selection of environmentally sustainable product designs.

The inherent uncertainty can be modeled using stochastic or simulation-based approaches. García-Diéguez et al. (2015) test the sensitivity of their fuzzy AHP model by means of Monte Carlo simulation. They investigate uncertainty in the fuzzy membership function's parameters and in the decision maker's preferences

(criteria weights). As a result, the sustainability scores of each alternative are represented as probability distributions. Ramanujan et al. (2014) use a stochastic simulation module within their AHP model to account for the variability in preferences among decision makers.

When evaluating the relative importance of the criteria, it may be desirable to involve the affected stakeholders. In this regard, AHP has the advantage that the scale used for pairwise comparisons is linked to easily understandable verbal descriptions. De Luca et al. (2015) present a participatory approach to SLCA that involves three stakeholder groups (workers, local community, and society) who are interviewed to select relevant criteria and to make the pairwise comparisons. Ramanujan et al. (2014) also incorporate judgements of expert groups and integrate a stochastic simulation module within AHP to account for the variability in preferences among the decision makers. The utility functions used for aggregation of parameter values in Lipuščček et al. (2010) are based on experts' findings that were gathered in a three-round Delphi method.

The *Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)* introduced by Hwang and Yoon (1981) is based on the principle that good alternatives should be as close to the ideal solution as possible and as far from the negative-ideal solution as possible. The ideal and the negative-ideal solution are generated as composites of the best and worst performance values exhibited by all alternatives. The proximity to each of these performance poles is measured via Euclidean distance measured with optional weighting of each attribute (Seppälä et al., 2001). A recent review of TOPSIS applications is provided by Behzadian, Khanmohammadi Otaghsara, Yazdani, and Ignatius (2012).

TOPSIS-based approaches have been applied in 11 articles of this review. Several useful extensions of TOPSIS and combinations with other methods have been proposed. AHP is integrated into TOPSIS by Gao, Liu, Hu, Zhang, and Gu (2010), Ng and Chuah (2012), and Pires, Martinho, Ribeiro, Mota, and Teixeira (2015) for a systematic determination of criteria weights. Back-propagation neural networks (BPNN) are used by Chiang, Che, and Wang (2011) to estimate the material and energy consumption of different design options for an optical mouse based on the product attributes and previous life cycle inventory data. A triple bottom line sustainability assessment model based on economic input–output analysis is adopted by Kucukvar, Gumus, Egilmez, and Tatari (2014) and Onat, Gumus, Kucukvar, and Tatari (2016). Group TOPSIS is applied in the same articles to integrate the preferences of multiple decision makers. The life cycle sustainability triangle (Finkbeiner, Schau, Lehmann, & Traverso, 2010; Hofstetter et al., 1999) is used by Onat et al. (2016) for a better visualization of the results and an analysis how the decision maker's priorities can influence the ranking and the perceived sustainability performance.

Different fuzzy TOPSIS approaches are used to deal with vague and imprecise data. Most often, criteria values and weights are described by linguistic terms that are linked to fuzzy numbers. Triangular fuzzy numbers based on traditional fuzzy set theory (Zadeh, 1965) are employed by Feng and Mai (2016), Gao et al. (2010), Ng and Chuah (2012), Wang and Chan (2013), and Wang, Chan, and Li (2015b). As an extension, intuitionistic fuzzy numbers (Atanassov, 1986), which quantify degrees of membership and non-membership to a set, are employed by Kucukvar et al. (2014) and Onat et al. (2016). Neutrosophic linguistic numbers, an even more generalized but also debated concept that integrates differences in semantics, are applied by Tian, Wang, Wang, and Zhang (2016). An alternative approach to modeling uncertainty is pursued by Huang, Zhang, Liu, and Sutherland (2011) who adopt the entropy method to modify the weighting factors based on unreliability and disorder in the data.

Outranking methods are based on pairwise comparisons of the alternatives against each other or a predefined norm. To this end, preference relations are established based on performance differences between the alternatives in each of the assessment criteria. A variety of outranking methods with different aggregation procedures has been developed. Two popular groups are ELECTRE and PROMETHEE. In ELECTRE, concordance and discordance matrices, which determine the strengths and weaknesses of alternatives based on the considered attributes, are analyzed to determine the order of alternatives, and in PROMETHEE, positive and negative outranking flows are calculated to obtain the ranking. Outranking methods are partially compensatory because the preference relations prevent compensation between particular attributes once a preference threshold of an attribute is exceeded. Comprehensive literature reviews on methodologies and applications are provided by Govindan and Jepsen (2016) for ELECTRE and by Behzadian, Kazemzadeh, Albadvi, and Aghdasi (2010) for PROMETHEE.

Fifteen articles of this review are related to outranking methods. ELECTRE TRI, a special version of ELECTRE that enables the categorization of alternatives into a set of pre-defined classes, is used by Domingues et al. (2015) to classify light-duty vehicles according to their environmental performance and by Tervonen et al. (2009) as well as Cinelli et al. (2017) for the classification of nanoparticles. PROMETHEE is used by Geldermann and Rentz (2005) to investigate alternative scenarios for industrial coating of mobile phones and automotive components. Two methodological variants of PROMETHEE are applied: PROMETHEE I, resulting in a partial preoder of alternatives based on positive and negative outranking flows, and PROMETHEE II, resulting in a total preoder of alternatives based on net outranking flows. Both PROMETHEE variants are applied by Le Téno and Mareschal (1998) for comparing the design of building products, by Parajuli, Knudsen, and Dalgaard (2015) for the pre-screening of potential biomasses as feedstocks for biorefineries, and by Schmitt et al. (2017) for comparing the sustainability of local and global food products. PROMETHEE I is used by Boufateh, Perwuelz, Rabenasolo, and Desodt (2011) to obtain a ranking of different fiber types for a t-shirt. PROMETHEE II is used by Samani, Mendes, Leal, Miranda Guedes, and Correia (2015) to identify the most sustainable sandwich-structured composite for novel housing solutions and Vukelic et al. (2017) to select an optimal knee support. A stochastic approach to PROMETHEE is proposed by Rogers and Seager (2009) to rank alternative transportation fuels.

To enhance the interpretation of the assessment results, Le Téno and Mareschal (1998) suggest using PROMETHEE with the Geometrical Analysis for Interactive Assistance (GAIA) (Mareschal and Brans, 1988). The idea behind GAIA is to project the multi-dimensional alternatives onto a two-dimensional plane that is calculated using Principal Component Analysis. This graphical representation, which allows for an easy identification of families of similar alternatives as well as groups of conflicting criteria, is also applied by Boufateh et al. (2011) and Vukelic et al. (2017).

Different approaches to deal with uncertainties within outranking methods have been implemented. Rather than selecting precise criteria weights, Domingues et al. (2015) define feasible weight vectors that obey certain constraints concerning, for example, the maximum acceptable ratio between any two weights. Thus, the result of their analysis is not a crisp classification of each alternative into a single class but rather a set of possible classes. This allows the decision maker to draw more robust conclusions that are independent of specific assumptions on the weights. Gheorghe and Xirouchakis (2007) present a fuzzy outranking method for evaluating product designs at their early stage of development according to different criteria. The imprecision about the design alternatives is modeled using triangular or trapezoidal fuzzy num-

bers. Alternatives are first compared within each criterion. Then, a fuzzy aggregation operator is applied to obtain global fuzzy outranking relations.

The Stochastic Multi-Attribute Life Cycle Impact Assessment (SMA-LCIA), an outranking method described by Rogers and Seager (2009), also addresses the uncertainty in criteria weights but uses a stochastic representation in combination with Monte Carlo simulation to explore feasible weight spaces. The method results in a rank acceptability index representing the probability that an alternative will be ranked first, second, third (and so on) as well as a central weights vector required for an alternative to be ranked first. This allows the decision maker to analyze the sensitivity of the rank ordering results to uncertainty, to eliminate alternatives with poor performance in all situations, and to prioritize research resources for reducing uncertainty. Rajagopalan, Venditti, Kelley, and Daystar (2017) apply SMA-LCIA to interpret the results of an LCA study on different feedstocks for biofuels. Motivated by the technological uncertainty associated with engineered nanomaterials, Canis, Linkov, and Seager (2010) expand the SMA-LCIA methodology by modeling uncertainty not only with regard to the criteria weights but also with regard to the performance attributes. Prado-Lopez et al. (2014) adopt the SMA-LCIA methodology for a comparative assessment of liquid and powder laundry detergents. They use the Pedigree matrix (Weidema & Wesnaes, 1996) to model the uncertainty in inventory data with regard to reliability, completeness, sample size, and temporal, geographical, and technological correlation. Finally, extensions to ELECTRE-TRI with the added capability of using imprecise measurement values, thresholds, weights, and class profiles are proposed by Tervonen et al. (2009) and Cinelli et al. (2017).

Another way to analyze the robustness of a ranking is proposed by Geldermann and Rentz (2005) who calculate sensitivity intervals that specify the domain in which the weighting factor for each criterion can be changed so that the overall ranking of alternatives remains unchanged. To address the imprecision that may prevail in the attribute values, Le Téno and Mareschal (1998) propose a modification to PROMETHEE that is based on intervals. In fact, this procedure is similar to fuzzy approaches and a defuzzification step is required to transform the results into a crisp ranking.

There are 6 remaining articles that apply other MADM methods, which cannot be matched to any of the groups above. Kadziński et al. (2018) propose an MADM model that incorporates ordinal regression to assess the implementation of green chemistry principles in nanoparticle synthesis protocols. Bachmann (2013) discusses how the development of LCSA can benefit from Multi-Criteria Decision Analysis (MCDA). The dominating alternative algorithm, which selects the best alternative out of a set by comparing two alternatives at a time using a dominance index, is compared to a total costs approach for a ranking of 26 future power generation technologies. Dhouib (2014) assesses reverse logistics options for waste tires using a fuzzy MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) model that allows for combining qualitative and quantitative information on the attractiveness of alternatives. Benetto, Rousseaux, and Blondin (2004) compare six scenarios for electricity production from an environmental point of view, and Naidu, Sawhney, and Li (2008) evaluate three manufacturing processes for nanoparticles based on eleven sustainability metrics using NAIADE (Novel Approach to Imprecise Assessment and Decision Environments), a multi-criteria method based on fuzzy pairwise comparisons, to integrate LCA results and to analyze uncertainty. Finally, Dorini et al. (2011) discuss the handling of uncertainty in multi-criteria decision making related to sustainability assessment. They propose a compromise programming model in which uncertainty is characterized using a probabilistic approach and propagated using Monte Carlo simulation.

The use of spatially differentiated data can be found in 21 articles that apply MADM methods. Most of these articles use weighting factors that reflect the preferences of particular stakeholder groups. For example, site-specific weighting factors based on local preferences are used by De Luca et al. (2015), Hosseinijou et al. (2014), and Lipušček et al. (2010), and site-dependent weighting factors reflecting the priorities in different countries are used by Kim, Hwang, and Park (2009) and Rochat et al. (2013). In this regard, MADM methods and in particular AHP have the advantage of systematic weight elicitation procedures. Site-dependent inventory data is used by Wulf et al. (2017) who compare alternative supply chains of rare earth permanent magnets and in articles that are based on national economic input-output tables (Kucukvar et al., 2014; Onat et al., 2016). National normalization references are used in Domingues et al. (2015).

The MADM methods that have been applied in the reviewed articles have proven to be useful for the aggregation of multiple criteria into a single score. One advantage of such systematic aggregation procedures can be seen in their ability to combine indicators from multiple sustainability dimensions that may even be measured on different scales. Furthermore, the systematic determination of criteria weights allows for integrating the preferences of different decision makers and stakeholders while simultaneously ensuring transparency in the assessment. The explicit use of spatially differentiated data or preferences within MADM models is sparsely found in the reviewed articles, opening options for future research.

4.2. Multi-Objective Decision Making (MODM)

Being a sub-discipline of MCDM, MODM is concerned with decision-making problems where multiple conflicting objectives have to be considered simultaneously and the set of alternatives is large and implicitly defined by constraints. Contrary to MADM, MODM rather deals with design problems and not with choice problems. Hwang, Paidy, Yoon, and Masud (1980) classify multi-objective optimization methods according to the stage of the optimization procedure at which the decision maker has to specify the preferences on the different objectives: never, a priori, a posteriori, or interactively during the procedure. Most commonly, optimization methods requiring an a priori or an a posteriori articulation of the preference information are used. A priori approaches (e.g., weighted-sum method, utility-function method, fuzzy-logic method, goal programming methods) scalarize the different objectives into one single objective function before the optimization problem is solved and only one solution is generated. In contrast, approaches with a posteriori information (e.g., multiple-run weighted-sum method; ε-constraint method, multi-objective genetic algorithms) determine a set of Pareto-optimal solutions. The selection of the "best" alternative out of the efficient solutions is then subject to the decision maker's individual and subjective preferences (Hwang et al., 1980).

The articles that use MODM for sustainability assessment of products are listed in Table 2. In these articles, MODM is used for product and/or process design decisions. Carreras, Boer, Cabeza, Jiménez, and Guillén-Gosálbez (2016); Doi, Chujo, Yoshimura, Nishiwaki, and Izui (2009); Michaud et al. (2009), and van Mierlo, Rohmer, and Gerdessen (2017) consider optimization of the design of a single product, Mangun and Thurston (2002) and Thurston and de la Torre (2007) focus on a portfolio of products, Tang, Wang, and Ullah (2016) on the selection of modules, and Manzardo et al. (2014) and Zhou, Yin, and Hu (2009) consider the selection of materials. Process design decisions mainly focus on the determination of an optimal life cycle pathway for a given product. For instance, Azapagic and Clift (1998, 1999) optimize the life cycle of boron products, Herrmann et al. (2014) and Tan, Culaba,

Table 2
Overview of articles applying MODM methods.

Authors and Year	Product	ECOL	ECON	SOC	Objectives	Approach	Methodological features
Ameli et al. (2016)	Waste cell phones	x	x	–	2	a posteriori	Stochastic optimization: simulation-based enumeration
Azapagic and Clift (1998)	Boron products	x	x	–	3	a posteriori	ε-constraint
Azapagic and Clift (1999)	Boron products	x	x	–	3	a posteriori	ε-constraint
Carreras et al. (2016)	Buildings	x	x	–	2	a priori	Multi objective genetic algorithm NSGA II with monetized objective function (eco cost)
Doi et al. (2009)	Milling machine	x	x	–	3	a posteriori	Normal-boundary intersection
Herrmann et al. (2014)	Biodiesel	x	–	–	5	a posteriori	Hypervolume estimation taboo search
Khan et al. (2001)	Vinyl chloride monomer	x	x	–	3	a posteriori	ε-constraint
Komly et al. (2012)	PET bottles	x	–	–	3	a posteriori	Multi objective genetic algorithm NSGA II + modified TOPSIS to identify preferred solution
Kravanja and Čuček (2013)	Biogas	x	x	–	2	a priori/a posteriori	ε-constraint/monetization (eco profit)
Mangun and Thurston (2002)	Personal computers	x	x	–	3	a priori	Utility function
Manzardo et al. (2014)	Pulp in paper industry	x	x	–	2	a priori	Weighted sum + TOPSIS to define objective function
Michaud et al. (2009)	Wood-plastic components	x		–	3	a posteriori	Particle swarm optimization
Ramadhan et al. (2014)	Palm-based biomass	–	x	x	2	a priori	Fuzzy logic
Tan et al. (2008)	Electricity, biofuels	x	–	–	2	a priori	Fuzzy logic
Tang et al. (2016)	Coal sample preparation system	x	x	–	2	a priori	Genetic algorithm with weighted-sum objective function
Thurston and de la Torre (2007)	Personal computers	x	x	–	3	a priori	Utility function
van Mierlo et al. (2017)	Meat replacers	x	–	–	4	a priori	Minsum/minmax
Zhou et al. (2009)	Drink containers	x	x	–	3	a priori	Genetic algorithm + artificial neural network to forecast fitness

and Aviso (2008) of biofuels, and Komly, Azzaro-Pantel, Hubert, Pibouleau, and Archambault (2012) of polyethylene terephthalate (PET) bottles. The approach typically requires the conduction of an LCA for a specific product or process first. Afterwards, the product/process system under consideration is optimized taking into account economic, environmental, and/or social criteria in order to improve the system's overall sustainability performance (Azapagic & Clift, 1999; Ramadhan et al., 2014). Ameli, Mansour, and Ahmadi-Javid (2016) integrate product and process design decisions by setting up an optimization model involving three different design options and four alternative end-of-life options for a cell phone (reuse, remanufacture, recycle, and dispose of) in the design stage of the product for a hypothetical company.

The number of objectives simultaneously considered in the optimization models ranges between two and five. Most often, ecological objectives (e.g., global warming potential, energy use, environmental impact) are balanced against economic (e.g., profit, life cycle costs) and/or rather technical objectives such as static compliance (Doi et al., 2009) or reliability (e.g., Mangun and Thurston, 2002). Five articles fully concentrate on different ecological objectives (Herrmann et al., 2014; Komly et al., 2012; Michaud, Castéera, Fernandez, & Ndiaye, 2009; Tan et al., 2008; van Mierlo et al., 2017). Only Ramadhan et al. (2014) consider a social objective by balancing work-related fatalities against life cycle costs.

About half of the MODM articles in this review make use of an a priori approach and generate a single solution. To this end, Mangun and Thurston (2002) and Thurston and de la Torre (2007) maximize a normative multi-attribute utility function, trading-off the attributes cost, reliability, and environmental impact. Fuzzy logic is utilized by Ramadhan et al. (2014) and Tan et al. (2008). Here, a continuous fuzzy degree of satisfaction is maximized subject to predetermined upper and lower limits of each objective/constraint. These limits are obtained by solving the corresponding single-objective optimization problems. For non-linear programs, which optimize complex design problems, single-objective (Tang et al., 2016; Zhou et al., 2009) or even multi-objective genetic algorithms are applied (Carreras et al., 2016). Thereby, Zhou et al. (2009) use an artificial neural network to forecast the fitness of material properties. Tang et al. (2016) define a weighted-sum objective function to balance GHG emissions and a customer satisfaction index. A similar approach is applied by Manzardo et al. (2014). They minimize the weighted distance from an ideal solution as known from TOPSIS where the ideal solution is determined by optimizing every single objective individually. Van Mierlo et al. (2017) first determine a payoff matrix by minimizing each indicator separately and then derive a minsum and a minmax objective function. Carreras et al. (2016) scalarize the objective function by means of monetization using the eco-costs indicator to quantify the cost of preventing a certain amount of environmental burden (Vogtländer et al., 2001). Monetization is additionally applied by Kravanja and Čuček (2013) who compute total profit as the sum of economic profit and eco-profit (difference between eco-benefits of unburdening the environment and eco-costs of burdening the environment).

Most of the work related to the a posteriori approach applies the ε-constraint method for the generation of a set of Pareto-optimal solutions (e.g., Azapagic & Clift, 1999; Khan, Natrajan, & Revathi, 2001). To this end, one objective is selected for optimization and the others are reformulated as constraints with varying ε defining the lower bound on the objective value. The starting value is derived by solving the corresponding single-objective optimization problems (Cohon and Marks, 1975). For their nonlinear multi-objective optimization problem of designing a milling machine, Doi et al. (2009) use the normal-boundary intersection method that allows determining evenly spread Pareto-optimal solutions. These solutions are identified at the intersection between the boundary of the set of feasible solutions and the normal to any point in the so-called convex hull of individual minima (Das & Dennis, 1998). Both the ε-constraint method and the normal-boundary intersection method require an iterative process to identify the Pareto front. An alternate approach is the Non-dominated Sorting Genetic Algorithm II (NSGA II) adopted by Komly et al. (2012) in which the Pareto front is obtained in one single run because of its ability to consider a population of

possible solutions (Deb et al., 2002). Michaud et al. (2009) develop a multi-objective particle swarm optimization to determine a set of Pareto-optimal solutions for eco-design problems. For the selection of a preferred solution out of the non-dominated ones, a modified TOPSIS approach is proposed by Komly et al. (2012).

Only Ameli et al. (2016) present a stochastic optimization model in which uncertain parameters such as usage duration, return time, and revenue generated from recovered products are taken into account when deciding about optimal design and end-of-life options for cell phones. In this model, three different risk measures are considered (expected value, value-at-risk, and conditional value-at-risk). The model is solved by means of an enumerative method that is based on Monte Carlo simulation and obtains a set of Pareto optimal solutions for a limited number of design alternatives. In all other articles, uncertainty is handled using sensitivity analyses, if at all. For instance, cost factors for the monetization of ecologic impacts (Carreras et al., 2016), objectives that are simultaneously integrated in the objective function (Khan et al., 2001; Kravanja & Čuček, 2013), weighting factors, or customer preferences (Mangun and Thurston, 2002; Thurston and de la Torre, 2007) are altered even though the uncertainty is not considered in a systematic manner.

Spatially differentiated data is used in 4 out of the 18 MODM articles. Carreras et al. (2016) optimize the thermal insulation of a building envelope for five different locations with varying climate conditions. Manzardo et al. (2014) and Tang et al. (2016) allow for sourcing the same materials or modules from different suppliers that vary in their performance regarding economic (e.g., price), ecological (e.g., water footprint, GHG emissions), and other factors (e.g., quality). For their case of producing green products from palm-based biomass, Ramadhan et al. (2014) distinguish between several plantations as a source of biomass, mills and biorefineries for the conversion of the biomass, as well as different customers for the green products. Thereby, the biomass potential, conversion rates, transport distances, customer demands, and especially the number of fatalities at every process stage are assumed to differ according to their location.

In summary, determining an optimal product design or an optimal life cycle pathway for a given product under consideration of economic, ecologic, and/or social objectives typically results in complex, non-linear, stochastic multi-objective optimization problems. The review of the articles indicates that MODM can generally facilitate sustainable product design and process decisions although stochastic optimization and spatial differentiation have drawn minor interest in literature so far. A posteriori methods have proven to be capable of obtaining a set of Pareto-optimal solutions when trading-off conflicting objectives related to the triple bottom line. However, the number of objectives that can be considered simultaneously is limited due to the increase in computational effort, making the selection of relevant objectives an extremely important task. The development of more efficient heuristics might be a promising approach to generating good solutions to such problems in future.

4.3. Data Envelopment Analysis (DEA)

DEA is a non-parametric approach for efficiency analysis of decision making units (DMUs), which seeks to compare DMUs to their best peers (efficient frontier). The basic model, first proposed by Charnes, Cooper, and Rhodes (1978), has been extended and applied in many ways. The application of DEA for sustainability assessment considers the sustainability indicators as inputs and outputs, and the DMUs are the alternatives to be assessed.

Table 3 lists the articles in this review that use DEA to analyze the eco- or socio-efficiency of products such as food and beverages, household appliances, and cars. In these studies, different products are compared based on their efficiency (e.g., Barba-Gutiérrez, Adenso-Díaz, & Lozano, 2009; Lozano, Adenso-Díaz, & Barba-Gutiérrez, 2011; Zhu, Wang, & Zhang, 2014). Assessments of alternative product designs, production processes, and supply chains for the same product are carried out by, e.g., Chen, Zhu, Yu, and Noori (2012), Martín-Gamboa, Iribarren, Susmozas, and Dufour (2016), and Sanjuan et al. (2011).

DEA models can be input- or output-oriented. Input-oriented models seek improvements in efficiency by minimizing the inputs levels while keeping output levels constant. In contrast, output-oriented models aim at maximizing the output levels while inputs are fixed. The majority of the articles analyzed use input-oriented DEA models. Only two articles apply an output-oriented approach (Hwang, Chen, Chen, Lee, & Shen, 2012; Rebolledo-Leiva, Angulo-Meza, Iriarte, & González-Araya, 2017), and three articles apply both input- and output approaches (Korhonen and Luptacik, 2004; Limleamthong et al., 2016; Picazo-Tadeo, Beltrán-Esteve, & Gómez-Limón, 2012). Furthermore, DEA models can also be differentiated into constant returns-to-scale (CRS), if changes in inputs are proportional to changes in outputs, and variable returns-to-scale (VRS). CRS is the predominant variant occurring in articles covered in this review which is usually assumed when the DMUs function in a competitive market.

Most articles using DEA address both the environmental and the economic dimension of sustainability. Eco-efficiency is, in these cases, defined as the ratio of the economic product value (often approximated by its price) to the environmental impacts related to the product (Barba-Gutiérrez et al., 2009; Lozano et al., 2011). Social aspects are additionally integrated by Galán-Martín et al. (2016) and Izadikhah and Saen (2017).

The basic DEA methodology can be enhanced by several extensions. For a further differentiation of efficient DMUs, super-efficiency analysis (Andersen & Petersen, 1993) is applied by Irribaren et al. (2010, 2010, 2011), Limleamthong et al. (2016), and Vázquez-Rowe, Villanueva-Rey, Iribarren, Teresa Moreira, and Feijoo (2012). It allows for ranking the efficient DMUs by assigning them efficiency scores greater than one. A ranking of efficient DMUs can also be obtained by integrating the order-of-efficiency concept (Das, 1999), which is particularly useful when a large number of criteria is analyzed (Galán-Martín et al., 2016). The concept is based on the repeated application of a standard DEA model for different combinations of indicators in each sustainability dimension. While the endogenous optimization of weighting factors within DEA reduces external bias, it may lead to unrealistic weighting factors. Therefore, Tatari and Kucukvar (2012) and Wier et al. (2005) add additional constraints to the DEA model in order to enforce more realistic bounds while still allowing for some flexibility. Finally, the product systems that are represented as DMUs in DEA models are often viewed as black boxes with inputs and outputs, assuming a rather aggregate perspective. More detailed analyses of internal system structure are enabled by Network DEA (Färe & Grosskopf, 2000; Kao, 2014). A two-stage Network DEA is applied by Chen et al. (2012) to analyze the sustainable design performance of an “industrial design” module and a “bio-design” module. Similar approaches are presented by Mahdiloo, Jafarzadeh, Saen, Tatham, and Fisher (2016) for car designs and by Zhu et al. (2014) for the production and use stage of pesticides.

Although stochastic and fuzzy approaches to DEA are available (Dyson & Shale, 2010; Hatami-Marbini, Emrouznejad, & Tavana, 2011; Olesen & Petersen, 2016), only few of the articles in this review consider uncertainty or vagueness. Most notably, Ewertowska et al. (2017) use a stochastic DEA model to evaluate the environmental efficiency of products under uncertainty. Their results show that the efficiency scores obtained from the stochastic model can differ significantly from the scores obtained from the deterministic model. Izadikhah and Saen (2017) incorporate stochastic data into

Table 3
Overview of articles applying DEA.

Article	Product/DMUs	ECOL	ECON	SOC	DMUs	Inputs	Outputs	Input-oriented	Output-oriented	CRS	VRS	Methodological features
Barba-Gutiérrez et al. (2009)	Electric/electronic appliances	x	x	–	9	3	1	x	–	—	x	–
Chen et al. (2012)	Car designs	x	–	–	23	4 + 2	2 + 4	n.a.	n.a.	x	x	Two-stage network DEA
Ewertowska et al. (2017)	Electricity (generation technologies)	x	–	–	11	9	1	x	–	–	x	Stochastic DEA
Galán-Martín et al. (2016)	Electricity (generation technologies)	x	x	x	8	18	1	x	–	x	–	Order of efficiency concept
González-García et al. (2015)	Fishing vessels	x	x	–	20	3	1	x	–	x	–	–
Hwang et al. (2012)	Car designs	x	–	–	2500	6	2 + 4	–	x	–	x	Undesirable outputs
Iribarren et al. (2011)	Dairy farms	x	x	–	72	7	6	x	–	x	–	Super-efficiency analysis, undesirable outputs
Iribarren, Martín-Gamboa, and Dufour (2013)	Electricity (wind farms)	x	x	–	25	5	1	x	–	x	–	–
Iribarren et al. (2010)	Mussel cultivation sites	x	–	–	67	9	1	x	–	x	–	Super efficiency analysis
	Fishing vessels	x	–	–	21	3	1	x	–	x	–	Intra- and intra sectorial assessment
	Fishing vessels	x	–	–	15	3	1	x	–	x	–	Enhanced economic dimension
	Fishing vessels	x	–	–	10	3	1	x	–	x	–	Window analysis
Izadikhah and Saen (2017)	Pasta	x	x	x	27	2 + 5	2 + 5	n.a.	n.a.	x	–	Chance-constrained two-stage DEA
Korhonen and Luptacik (2004)	Electricitiy (power plants)	x	x	–	24	1	1 + 3	x	x	x	x	Multiple DEA models, undesirable outputs
Kortelainen and Kuosmanen (2007)	Car models	x	x	–	88	5	1	x	–	x	x	Absolute shadow prices
Limleamthong et al. (2016)	Solvents	x	–	–	125	9	1	x	x	–	x	Super-efficiency analysis
Lozano et al. (2011)	Electric/electronic appliances	x	x	–	9	3	1	x	–	–	x	–
Lozano et al. (2009)	Mussel cultivation sites	x	–	–	62	14	1	x	–	x	x	–
Mahdiloo et al. (2016)	Car designs	x	–	–	23	4 + 2	2 + 4	n.a.	n.a.	x	x	Multi-criteria two-stage DEA
Martín-Gamboa et al. (2016)	Biohydrogen	x	–	–	19	5	1	x	–	x	–	–
Picazo-Tadeo et al. (2012)	Olive farms	x	x	–	55	4	1	x	x	x	–	Directional distance functions
Rebolledo-Leiva et al. (2017)	Organic blueberries	x	x		14	5	2	–	x	–	x	–
Sanjuan et al. (2011)	Cheese production scenarios	x	x	–	16	3	1	x	–	x	–	Monte Carlo Simulation for sensitivity analysis
Tatari and Kucukvar (2012)	Wall finishes	x	x	–	11	9	1	x	–	x	–	Weight restrictions
Vázquez-Rowe et al. (2012)	Vineyards	x	–	–	40	10	1	x	–	x	–	Super-efficiency analysis
Wier et al. (2005)	Commodities in households	x	–	–	11	7	1	x	–	x	–	Weight restrictions
Yang, Lu, Guo, and Yamamoto (2003)	Refrigerators	x	x	–	4	12	3	x	–	x	–	–
Zhu et al. (2014)	Pesticides	x	x	–	10	3 + 1	1 + 1	n.a.	n.a.	x	–	Network DEA

* = multiple (not specified); n.a. = not applicable

a two-stage DEA model with undesirable outputs. Sanjuan et al. (2011) carry out sensitivity analysis using Monte Carlo simulation to test the influence of price changes on the eco-efficiency of different production scenarios for Mahón-Menorca cheese. They perform 10,000 simulation runs with varying prices and record the number of times each production scenario is considered eco-efficient. Korhonen and Luptacik (2004) investigate how different modeling approaches within DEA influence the eco-efficiency of power plants. In their case, the choice of a model variant influences the eco-efficiency scores, but efficient units are efficient in all model variants. Finally, Zhu et al. (2014) analyze the shadow prices from the DEA model to reveal its sensitivity to changes in the input and output indicators.

DEA is used for site-specific sustainability assessments in 12 articles. Most often, different production sites and supply chains for a given product are compared. For example, González-García et al. (2015) compare the efficiency of 20 Portuguese fishing vessels, Picazo-Tadeo et al. (2012) analyze a sample of 55 olive-growing farms in Southern Spain, and Vázquez-Rowe et al. (2012) analyze the grape production in 40 specific vineyards in Northwestern Spain. The surrounding conditions at specific locations are also considered by Tatari and Kucukvar (2012) who analyze the eco-efficiency of construction materials.

Based on the articles reviewed, we observe that DEA is a useful tool for eco-efficiency assessment for large sets of alternatives but a limited number of criteria. It is applied to identify efficient production sites, to set target efficiency levels for currently inefficient sites, and to estimate the environmental and economic benefits of moving towards efficiency. Taking the endogenously derived efficient frontier as a reference for improvement, however, also has some drawbacks. It neither allows for deriving improvement recommendations for already efficient units nor does it allow for judgements whether a state of sustainability would be achieved if all units operated efficiently.

4.4. Other methods

Various other Operations Research methods that facilitate sustainability assessment have been applied in the remaining 13 articles (Table 4). The subsequent discussion of these articles is structured according to the challenges which they address. Beginning with the selection of relevant indicators, Gutierrez, Lozano, Moreira, and Feijoo (2010) propose the use of statistical multivariate analysis techniques such as Principal Component Analysis (PCA) and Multi-Dimensional Scaling (MDS). PCA allows for reducing the dimensionality of a data set with several related

Table 4
Overview of articles applying other methods.

Authors and Year	Product	ECOL	ECON	SOC	Attributes	Methodological features
Bovea and Wang (2003)	Office table	x	–	–	1	Fuzzy QFD
Gutierrez et al. (2010)	Mussels	x	–	–	10	Principal Component Analysis, Multi-Dimensional Scaling
Gonzáles et al. (2002)	Lamp	x	–	–	6	Fuzzy inference system
Halog (2004)	Light fitting system	x	x	–	3	Fuzzy linguistic decision support system
Hanes et al. (2015)	Ethanol	x	–	–	1	Comprehensive allocation investigation strategy
Jeong and Lee (2009)	LCD panel	x	x	–	2	Monetization: Conjoint Analysis
Krieg et al. (2013)	Mulit-use plastic crates	x	x	–	3	Monetization: Shadow prices from SIMPLEX
Kuo et al. (2016)	Network router	x	–	–	9	Depth-first search
Kuo et al. (2009)	Toner cartridge	x	–	–	3	Fuzzy QFD
Prado-Lopez et al. (2016)	Photovoltaic panels	x	–	–	18	Overlap area approach
Santhanam and Gopalakrishnan (2013)	Road pavement	x	–	–	6	Qualitative approach with logical inference
Su et al. (2012)	Office chair	x	x	–	2	Bi-level optimization: genetic algorithm + dynamic programming
Tambouratzis et al. (2014)	Liquid container	x	–	–	4	Artifical neural networks, genetic algorithms

variables into a smaller data set of uncorrelated variables. MDS generates graphical representations of relationships among stimuli that can be used for identifying and summarizing similar indicators. Prado-Lopez et al. (2016) use a probability distribution-based approach to assess the significance of performance differences among alternatives that allows LCA practitioners to focus their analysis on those aspects that are most influential to the decision.

The comparison of alternative products is facilitated in different ways. Monetary valuation is applied to convert sustainability impacts (measured in different units) to a common monetary scale. To determine the monetary value of environmental impacts, Jeong and Lee (2009) use Conjoint Analysis and Krieg, Albrecht, and Jäger (2013) use shadow prices that can be obtained from the SIMPLEX algorithm. An alternative approach that compares products based on qualitative judgements of the decision maker is proposed by Santhanam and Gopalakrishnan (2013). It adopts logical inference to avoid subjective weighting and to facilitate the interpretation of the results by the decision maker.

Addressing the issue of uncertain and incomplete data, methods to obtain preliminary estimates of the product-related sustainability impacts are proposed. Gonzáles, Adenso-Díaz, and González-Torre (2002) develop a streamlined method for impact assessment in LCA making use of fuzzy logic to avoid the need for in-depth environmental knowledge and extremely accurate data, making it a practicable tool for small- and medium-sized enterprises with limited resources. Streamlined assessments also integrate Quality Function Deployment (QFD) to identify customer preferences and fuzzy logic to deal with imprecise information regarding the product's environmental, financial, and technical performance (Bovea & Wang, 2003; Halog, 2004; Kuo, Wu, & Shieh, 2009). The prediction of environmental impacts of new products based on depth-first search is proposed by Kuo, Smith, Smith, and Huang (2016). Their methodology facilitates early stages of an eco-design process by matching new product designs to previous designs, searching similarity graphs, separating designs into groups, and predicting environmental impacts from previous designs. The approach of Tambouratzis et al. (2014) estimates the environmental impacts of different materials from their properties using artificial neural networks and identifies the properties of a maximally sustainable material for a given application using genetic algorithms. A decision support system to estimate the CO_2 emissions and cost of product designs adopting an evolutionary-based genetic algorithm and dynamic programming is developed by Su, Chu, and Wang (2012). Uncertainty in inventory analysis also arises when multi-functional processes are involved and allocation is required. Hanes, Cruze, Goel, and Bakshi (2015) address the problem of arbitrarily chose allocation criteria by developing a Comprehensive Allocation Investigation Strategy (CAIS) based on linear model theory to examine any given inventory under all possible allocation decisions.

Only one article proposes a notable approach for spatial differentiation. Namely, Krieg et al. (2013) determine organization-specific shadow prices for environmental impacts.

5. Promising approaches and research needs

In this section, we synthesize the typical application scenarios for product sustainability assessment, highlight the promosing approaches from Operations Research, and explain how they can be used to address the key challenges in sustainability assessment. This is followed by a discussion where further research is needed.

5.1. Application scenarios

The typical application scenarios of product sustainability assessment can be subsumed under three groups (Table 5): the development of new products, the improvement of existing products, and the evaluation of products. The *development of new products* is in the focus of many articles because the future sustainability performance of a product can be influenced significantly during its development stage. Since conducting LCSA at this stage is difficult due to limited data availability and significant uncertainties, methods to obtain rough estimates of the results are applied. For example, the sustainability impacts of a new product are approximated from previous product designs or material properties using neural networks (Chiang et al., 2011; Tambouratzis et al., 2014) or depth-first-search (Kuo et al., 2016). Often, multiple design alternatives of the new product are developed and the best alternative from a sustainability perspective must be selected. This is usually done by MADM models. In some cases, it is also possible to find functional relationships between the product attributes and its sustainability impacts, which allows for the generation of optimal product designs by application of MODM models (e.g., Doi et al., 2009; Michaud et al., 2009; Tang et al., 2016).

The *improvement of existing products* usually starts with an assessment of their improvement potential. Specific improvement targets can be formulated by comparing the current sustainability performance with the efficient frontier derived in DEA models (e.g., Galán-Martín et al., 2016; Iribarren, Vazquez-Rowe, Moreira, & Feijoo, 2010; Lozano, Iribarren, Moreira, & Feijoo, 2009). For the exploration of improvement options, MODM models are used to

Table 5
Application scenarios for Operations Research methods in sustainability assessment.

Application scenario	Number of articles*	Sustainability dimensions			Number of indicators			Type of OR method				Purpose of OR method		
		ECOL	ECON	SOC	Low (<5)	Medium (5-10)	High (>10)	MADM	MODM	DEA	Other	Enable LCSA	Complement LCSA	Substitute LCSA
Development of new products														
Estimation of sustainability impacts	2	●	○	○	○	●	○	◑	○	○	◑	○	○	●
Selection of best design from set of alternatives	27	●	◑	○	◑	◑	○	●	○	○	○	○	◑	◑
Generation of optimal product design	14	●	◑	○	◑	◑	○	○	●	○	○	○	●	○
Improvement of existing products														
Estimation of improvement potential	13	●	◑	○	◑	◑	○	○	○	●	○	○	●	○
Exploration of improvement options	5	●	◑	○	◑	◑	○	○	●	○	○	◑	◑	○
Selection of best improvement option	6	●	◑	○	◑	◑	○	◑	○	○	◑	◑	◑	◑
Evaluation of products														
Prioritization of the major sustainability drivers	18	●	◑	◑	○	◑	◑	◑	○	○	◑	○	◑	◑
Comparison of alternative products	72	●	◑	◑	◑	◑	◑	◑	○	◑	○	◑	◑	◑
Classification of product to predefined set of classes	2	●	○	○	○	●	○	●	○	○	○	○	●	○

*) n=142. Some articles cover multiple application scenarios. ● applies to most articles (>80% of the articles covering that application scenario), ◑ to some articles (20% – 80%), ○ to few or no articles (<20%).

find a range of Pareto-optimal solutions (e.g., Azapagic & Clift, 1998, 1999; Carreras et al., 2016). For the selection of the best improvement option, MADM models (e.g., Pineda-Henson, Culaba, & Mendoza, 2002; Ramzan, Degenkolbe, & Witt, 2008) or approaches based on monetization (e.g., Jeong & Lee, 2009) are used.

The *evaluation of products* is the most prevalent application scenario in the articles reviewed. Some of the proposed methods focus on prioritizing the sustainability drivers of a product with regard to the sustainability impacts, the product components, or its life cycle phases. To this end, MADM methods like AHP (e.g., Bereketli Zafeirakopoulos & Erol Genevois, 2015) or other methods like Principal Component Analysis (e.g., Gutierrez et al., 2010) are applied. The comparison of alternative products is often facilitated by MADM and DEA models. Products can not only be compared to other products but also be assigned to a predefined set of classes using outranking methods (e.g., Cinelli, Coles, & Kirwan, 2014; Domingues et al., 2015).

The application of Operations Research methods fulfills different purposes in relation to the life cycle-based sustainability assessment methods that are integrated under the LCSA framework. In some articles, the Operations Research methods are used to *enable LCSA*, i.e., the Operations Research methods become an integral part of LCSA and solve particular problems such as allocation or weighting (e.g., Agarski et al., 2016; Azapagic & Clift, 1998; Hanes et al., 2015). In most cases, the Operations Research methods are applied to *complement LCSA*, i.e., the results from an LCSA study are used as an input to Operations Research methods, which facilitate their analysis and interpretation or combine them with other indicators in order to compute aggregate sustainability indices (e.g., Geldermann and Rentz, 2005; Lozano et al., 2009; Onat et al., 2016). Finally, some authors apply Operations Research methods to *substitute LCSA* in the sense of a streamlined assessment, for example, by generating rankings based on expert judgements as a starting point for more detailed life cycle-based analyses (e.g., Parajuli et al., 2015; Tian et al., 2016; Wang & Chan, 2013). Especially for comprehensive assessments of complex product systems, the application of Operations Research Methods to enable or complement the established life cycle-based methods appears to be a promising approach that not only receives considerable attention in many articles of this review but also in the conceptual advancement of sustainability assessment methods (Cinelli et al., 2014; Onat, Kucukvar, Halog, & Cloutier, 2017; Zamagni et al., 2009).

5.2. Key challenges and research needs

The application of Operations Research methods contributes to solving some of the challenges in sustainability assessment, yet there remains considerable need for further research. The key challenges to sustainability assessment, as discussed in Section 1, are the selection of relevant indicators/impact categories, the normalization and weighting of different criteria, the handling of uncertain and incomplete data, and the spatial differentiation in impact assessment.

The *selection of sustainability indicators* is not addressed systematically by most articles in this review. While hundreds of different indicators could be identified over the entire sample, only 9.5 indicators are used on average within a particular assessment. The average number is slightly higher in MADM models (11.9 indicators) and lower in DEA models (7.8 indicators) and MODM models (3.7 indicators). The indicators are often selected without justification, although the selection may influence the outcome of the assessment significantly. For example, from a comparison of the solutions to an MODM model with different sets of indicators as objective functions, Khan et al. (2001) find that the optimization of selected indicators does not necessarily improve the performance of other indicators. A systematic approach to analyze the relationships between sustainability indicators is proposed by Gutierrez et al. (2010) where multivariate statistical methods like PCA and MDS are applied to reduce the number of indicators without distorting the main features of the decision problem. In this regard, future research should attempt to better understand how the selection of indicators influences the assessment results and adopt more systematic selection procedures. The analysis of the indicators selected also reveals a bias towards environmental and economic indicators. Social aspects are only considered in 30 of 142 articles, all of which were published after 2008. This underscores the emerging integration of the triple bottom line of sustainability. However, because the set of potential social indicators is very large, justification of relevant indicators becomes even more important.

The *comparison of alternative products* based on multiple criteria has been facilitated by Operations Research methods in many ways. MADM methods, which have been applied in 86 articles, are used to evaluate finite sets of alternatives. In most cases, a ranking of alternatives is obtained by comparing the aggregated sustainability scores. The aggregation procedures used in different MADM methods typically involve normalization and weighting steps that integrate the decision maker's preferences in a systematic way. By far the most popular method for weight elicitation is AHP (applied in 38 articles). Furthermore, it is even possible to include the preferences of multiple decision makers that may represent different stakeholder groups or contribute different expertise (e.g., De Luca et al., 2015; Dorini et al., 2011; Hosseinijou et al., 2014; Kucukvar et al., 2014; Lipušček et al., 2010; Tian et al., 2016). An emerging challenge is in the integration of semi-quantitative and qualitative

indicators, which are often used for assessing social sustainability issues. For this purpose, the application of ordinal classification methods like the recently proposed ELECTRE TRI-nB (Fernández, Figueira, Navarro, & Roy, 2017) appears useful. DEA models, which have been applied in 25 articles, are useful to compare alternatives without the explicit knowledge of the decision maker's preferences. However, discrimination among the efficient alternatives requires the integration of additional methods like super-efficiency analysis. The application of such methods can sparsely be found in the reviewed articles (e.g., Iribarren et al., 2011; Vázquez-Rowe et al., 2012), and especially the application of more recent approaches to increase the discriminatory power of DEA based on cooperative games (Li, Xie, Wang, & Liang, 2016) or weighted goal programming (Rubem et al., 2017) appears promising and deserves further investigation. From the 18 articles in which MODM methods have been applied, about half uses a priori approaches whereby the different objectives are scalarized based on the decision makers preferences to determine one optimal solution, and half uses a posteriori approaches that generate a set of Pareto-optimal solutions from which the preferred solution is selected by the decision maker. Although there is no theoretical limitation, the number of objectives that can practically be handled in MODM models is limited. In fact, the number of objectives considered by the MODM articles in this review ranges between 2 and 5, which is much smaller than the number of criteria that are typically considered in sustainability assessments. Hence, there is a need to employ advanced MODM solution procedures like the multi-objective branch and bound algorithm (Przybylski & Gandibleux, 2017) that are capable of handling more objectives simultaneously while keeping the computational effort at a reasonable level.

The numerous *uncertainties* inherent to sustainability assessment are only considered in about half of the reviewed articles. The main sources of uncertainty are the inventory data and the decision makers' preferences. Both sources of uncertainty are most often addressed by means of sensitivity analysis. In addition, MADM models have been complemented with fuzzy logic and simulation-based approaches. Fuzzy logic allows expression of imprecise inventory data and, more importantly, vague preference information as linguistic variables that are mapped to fuzzy numbers. However, the parameters used for this procedure induce additional uncertainty, which requires further investigation (García-Diéguez et al., 2015). Therefore, it appears more reasonable to analyze feasible weight sets directly using Monte Carlo simulation and to present the resulting sustainability scores as box plots or probability distributions, or to calculate the probabilities that an alternative achieves a certain rank (Prado-Lopez et al., 2014; Ramanujan et al., 2014; Rogers & Seager, 2009; Scott et al., 2016). DEA models eliminate one potential source of uncertainty as they do not require the decision maker to express preferences regarding the importance of the criteria. However, the remaining uncertainties related to input and output parameters are barely addressed by the articles in this review despite the availability of stochastic DEA approaches (Olesen & Petersen, 2016). Hence, there is a need for bridging the gap from the theoretical DEA works to the specific context the sustainability assessment. Similarly, a posteriori MODM methods determine all Pareto efficient solutions independent of the decision maker's preferences. Nevertheless, more systematic approaches to address the remaining uncertainties, such as stochastic and robust optimization models like the recently proposed approaches by Jornada and Leon (2016) or Hanks, Weir, and Lunday (2017), have not found broad application in sustainability assessment yet and deserve closer attention.

Spatial differences have generally received little attention by the articles in this review. The assessments in 102 articles are based on site-independent inventory data and generic criteria weights. Only 20 articles use site-specific and 20 articles use site-dependent data. Site-specific inventory data is mainly used in DEA models where explicit production sites of a product are compared (e.g., Iribarren et al., 2010; Lozano et al., 2009; Vázquez-Rowe et al., 2012). Site-specific inventory data is also used in some MADM and MODM articles that address social sustainability (De Luca et al., 2015; Hosseinijou et al., 2014; Ramadhan et al., 2014). In addition to that, site-specific weighting factors elicited from local sustainability experts have been integrated into MADM models (De Luca et al., 2015; Hosseinijou et al., 2014; Lipušček et al., 2010; Myllyviita et al., 2013; Ramanujan et al., 2014). On a coarser spatial resolution, site-dependent data has mainly been integrated into MADM models. For example, LCA data is derived from country-specific input-output tables (Kucukvar et al., 2014; Onat et al., 2016; Tatari & Kucukvar, 2012), national reference values are used for normalization (Domingues et al., 2015), and weighting factors reflecting the perspectives of different makers are investigated (e.g., Agarski et al., 2016; Bloemhof-Ruwaard, Koudijs et al., 1995; Gloria, Lippiatt, & Cooper, 2007; Hermann et al., 2007). Despite these efforts, the spatial distribution of sustainability impacts is hardly considered at the valuation stage. For example, the environmental impact of electricity use depends on the regional electricity mix, or the loss of manual labor in developing countries would have different consequences than in industrialized countries. Furthermore, a product that is evaluated as globally sustainable due to a lower overall impact score may aggravate the situation in a particular region. Therefore, appropriate methods that evaluate both global and local sustainability need to be developed.

6. Conclusion

In this paper, we survey how Operations Research methods have been applied to facilitate sustainability assessment of products. From the analysis of 142 articles, which were identified by a systematic search process, we observe that many methods from Operations Research are increasingly used to address challenges in sustainability assessment. The use of MADM, MODM, DEA, and other methods from Operations Research has introduced new perspectives into traditional sustainability assessment, increasing its comprehensiveness and providing new ways of communicating results, instead of merely presenting a list of performance indicators for the alternatives considered. This opportunity has been mainly recognized by the Environmental Management community. In contrast, the field of product-related sustainability assessment has received little attention by the Operations Research community and there is significant potential in the identification and analysis of practically relevant issues in this domain. By classifying the related articles according to their setting and the applied Operations Research methods, promising approaches and important research needs have been highlighted. The increasing requirement for the integration of social indicators in the assessment, leading to challenges with regard to the selection of indicators, the integration of semi-quantitative and qualitative indicators, and the simultaneous consideration of global and local sustainability objectives, are all avenues for future research. Furthermore, there remains considerable potential for the application of fuzzy and stochastic approaches to MODM and DEA to address the uncertainty inherent in the inventory data and the decision maker's preferences appropriately when conducting a sustainability assessment. Finally, it should also be recognized that challenges such as the selection of indicators, balancing incommensurable assessment criteria, and data quality issues require additional action outside the realm of Operations Research.

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Supplementary materials

The review database with detailed information on bibliographic data, sustainability dimensions and indicators, Operations Research methods, treatment of uncertainties, spatial differentiation, products, and application scenarios of each article can be found in the online version, at doi: http://dx.doi.org/10.1016/j.ejor.2018.04.039.

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